Abstract

This study presents the design, development and validation of an AI-based framework for weather-informed intercity travel advisories with the Mumbai–Pune corridor as a representative case study. The framework integrates multi-source weather and travel data including meteorological records, real-time satellite feeds, and traffic sensor logs into a structured geo-tagged dataset enabling high-resolution route-specific analysis. A hybrid deep learning model leveraging convolutional recurrent and graph neural network components is trained to forecast short and medium-term weather along critical travel routes. A retrieval-augmented generation (RAG) system processes real-time advisories and traffic alerts dynamically synthesizing actionable travel recommendations. An LLM-driven conversational interface translates technical forecasts into clear personalized travel guidance fostering greater user trust and compliance.

Empirical evaluation including cross-validation and field trials during monsoon conditions demonstrates superior forecast accuracy, advisory relevance and system usability compared to traditional approaches. The proposed framework reduces weather-related travel disruptions, improves journey time predictability and enhances overall traveller satisfaction. Key contributions include the creation of a robust geo-tagged dataset for the Mumbai–Pune route. A validated end-to-end advisory system, and open resources for broader adoption. The results highlight the potential for AI-powered weather-centric advisory solutions to support weather-resilient efficient and safe intercity travel.

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Title: Development of an AI-Based Framework for Weather-Informed Intercity Travel Advisories.

1. Introduction:

Modern intercity travel on busy routes such as Mumbai–Pune often faces serious difficulties due to unpredictable weather. Heavy rainfall, dense fog, and sudden changes in climate not only create safety risks but also disrupt travel plans. At present, most travel advisory systems react only after problems arise, relying on outdated or delayed information. As a result, travellers are left without timely guidance, which frequently leads to traffic congestion, unexpected delays, and unpleasant travel experiences with the rapid progress of artificial intelligence and data analytics, there is now an opportunity to rethink how travel guidance is provided. By integrating weather data from multiple sources with real-time traffic updates and digital maps, it is possible to design systems that can predict weather-related risks and assess their likely impact on specific routes. Such systems can highlight potential problems in advance and offer practical insights to travellers, transport operators, and authorities for better planning and decision-making.

This study focuses on building an AI-driven framework tailored for weather-related travel advisories along the Mumbai–Pune corridor. A crucial transport link that experiences diverse weather conditions throughout the year. The proposed model will collect and process a wide range of weather and traffic data, combine it with location-based mapping, and generate route-specific insights. An intelligent forecasting module will be developed to predict weather conditions, while advanced algorithms will be used to produce real-time alerts and travel recommendations. To make the system more accessible, a conversational interface supported by large language models will be included. This interface will simplify complex weather information, ensuring that users receive clear and trustworthy advice. The expected outcomes include the creation of a structured database of weather and travel patterns for the corridor, the development of a tested prediction model capable of generating accurate advisories, and a user-friendly platform that delivers actionable recommendations.

Through this approach, the research seeks to combine data-driven analysis, advanced prediction techniques, and effective communication into a single advisory system. The ultimate aim is to improve travel safety and reliability, particularly as India continues to face increasingly uncertain weather conditions.

2. Aim of Study:

This study focuses on creating and validating a comprehensive AI-powered system that brings together weather and travel data from multiple sources, enhanced by precise geo-tagging techniques, to generate accurate and real-time weather forecasts and smart travel advisories for intercity routes. Taking the Mumbai–Pune corridor as an example, the research aims to develop a complete solution that combines advanced deep learning models for weather prediction, a retrieval-augmented generation system to produce timely travel alerts.

3. Objectives of Study:

The primary objectives of this research are centred around developing a comprehensive AI-driven solution for weather-based intercity travel advisory systems. This involves creating a robust data integration and preprocessing pipeline that transforms heterogeneous weather and travel information into a structured, geo-tagged dataset tailored for corridor-specific analysis.

The Objectives of this Research:

1. To integrate and pre-process multi-source weather and travel data, applying geo-tagging to routes for creating a structured, location-centric dataset, with Mumbai–Pune and vice versa selected as the case study.

2. To develop an efficient AI-based forecasting model that predicts weather conditions along intercity routes,

3. To develop a RAG-enabled travel advisory framework for real-time weather advisories and travel alerts.

4. To build an LLM-driven advisory interface that communicates weather-based travel guidance.

4. Study Background (Literature Review) and Significance of study

Literature Review:

This work reviews the core concepts of transparency and explainability in intelligent agent communication. Applied to travel advisory, such transparency frameworks are crucial for building contextual LLM-driven interfaces user's trust. The gap lies in integrating high-frequency weather and mobility alerts with on-demand, user-focused explanations for intercity travel[1].

Extends GNNs for hierarchically modelling spatial weather variables, improving context-aware travel advisory. Gap: real-time integration with route-centric datasets and LLM advisory systems[2].

A survey of AI methods for extreme weather prediction, emphasizing probabilistic approaches and hybrid frameworks. For Mumbai–Pune, AI's challenge is in integrating short-term route alerts with accurate risk quantification for commuters[3].

This work reviews impact-based AI warning systems for local and regional weather disruptions. Gaps remain in personalized advisories along critical travel corridors, and in validating real-time effects on traffic and logistics[4].

Road weather modelling using vehicle sensors and AI for high-resolution travel safety forecasts. Approach supports geo-tagged route-level analysis (such as Mumbai–Pune), but requires expansion to multi-city corridors and integration with travel demand data[5].

Proposes Bayesian neural networks for probabilistic weather forecasts using historical atmospheric data, demonstrating improved reliability. Framework gaps: application to intercity routes and coupling predictions with travel risk analytics[6].

Explores the use of integrated AI systems for multi-hazard early warning. Relevance for Mumbai–Pune: highlights need for integrated geo-tagged datasets and impact-focused advisory mechanisms; gap in actionable, corridor-specific real-time risk alerts[7].

Examines diffusion-based generative AI models for precipitation nowcasting, offering uncertainty estimates for travel hurdles. Needs adaptation and validation for Mumbai–Pune with multi-source, fine-grained historical datasets[8].

Applies ConvLSTM to nowcasting, emphasizing time-series spatial modelling. Offers improvements for forecasting along expressways, yet needs further geo-tagging of vehicular and environmental data for travel advisory systems[9].

This paper presents an innovative approach for continuous road weather monitoring using AI calibration of vehicle-mounted sensor networks. The methodology employs machine learning algorithms to process large volumes of real-time data from fleet vehicles equipped with temperature, humidity, and precipitation sensors along intercity routes. The AI system calibrates physical road weather models and generates timely warnings about dangerous conditions such as ice formation, heavy rain, and snow accumulation. However, the study reveals significant gaps in geo-spatial coverage for rural intercity segments and lacks integration with travel advisory communication systems. The research does not address route-specific prediction accuracy or user interface design for delivering actionable travel guidance to intercity travellers [10].

Advanced graph neural model for station-based and route-based prediction, supports geo-tagging and location-centric advisory. Need: end-to-end validation on the Mumbai–Pune corridor with integrated travel alerts[11].

Features adaptive graph neural modules for regional weather, improving structural representation critical for travel advisory. Gaps persist in linking to multi-source travel data for highly contextualized recommendations[12].

Uses multi-modal RNN to blend atmospheric and surface variables for nowcasting, crucial for route-specific advisory. Gap: LLM-driven explanations for model predictions to foster traveler trust[13].

MetNet-3 extends lead times and variables for real-time weather prediction using dense/sparse sensors. Integrating corridor data (Mumbai–Pune) and connecting to LLM-based advisory chatbots remains a future challenge [14].

The work develops a hybrid NWP/ML system—combining physics-based climate models with machine learning techniques—capable of short-range, local weather predictions. This methodology proves effective for travel forecasting where rapid weather changes occur. The research calls for further integration of real-time travel demand and traffic data to help adapt forecast models for intercity corridor decision support. Lack of travel-specific variables in prediction models; future work required on road/weather interaction and travel-time prediction using AI[15].

Introducing NeuralGCM, a differentiable atmospheric solver coupled with ML components for high-resolution forecasting, this study achieves superior RMSE and bias scores essential for

accurate route-level travel weather planning. While NeuralGCM provides ensemble forecasts relevant for assessing travel risks (storms, cyclones), the study points out its relatively coarse output resolution and the challenge of translating large-scale predictions to route-specific and hourly travel contexts. Conversion of global/ensemble predictions to actionable, route-level advisories for travellers remains an open research area[16].

Employing LSTM and hybrid neural approaches, this study demonstrates improved accuracy for time-series weather forecasting by fusing real-time observations and historical trends, outperforming classical models in diverse scenarios. The gap persists in hyperlocal, route-specific predictions and real-time adaptability required for intercity travel[17].

This work merges numerical weather prediction (NWP) with statistical learning for high-resolution forecast modelling, foundational for applications in travel weather risk management. The integration of additional real-time travel sensors and dynamic re-routing algorithms remains a challenge for direct intercity deployment[18].

Big data methods and ensemble machine learning improve regional forecast fidelity, which can underpin travel advisory systems. The present work is not tailored to intercity corridor prediction and needs adaptation for real-time decision making by commuters[19].

Focuses on scalable big data processing, the architecture holds promise for supporting live AI-driven travel route forecasting. The study highlights the gap in converting climate predictions into direct actionable decisions for travel, especially at the corridor and route segment level[20].

Presents an IoT-enabled architecture with hybrid AI algorithms for continuous, real-time weather monitoring, providing foundations for future intercity travel forecasting platforms. Scaling and route-specific contextualization remain open tasks[21].

Demonstrates how modern ML models (deep learning) can surpass legacy algorithms for short-term forecast accuracy, though the work does not address the challenges of integrating travel-related variables or providing real-time route advisories[22].

This survey identifies recent advances and persistent gaps, including the need for multimodal input fusion and real-time, route-level predictive solutions for travel planning[23].

Explores advanced neural model architectures for weather forecasting and highlights the limitations of scale and resolution for use in travel-specific decision support[24].

GenCast introduces scalable probabilistic models for rapid and highly accurate weather forecasting, outperforming classical NWP at medium range. However, direct deployment for corridor-specific travel remains to be tested[25].

Research Gap:

- **Corridor-Specific Data Integration and Geo-Tagging**

While numerous studies employ multi-source weather data fusion, very few focus on precise geo-tagging of route segments for intercity travel corridors. Existing frameworks often aggregate weather and travel data at broad regional scales, lacking the granularity required to model localized microclimates and travel conditions specific to corridors like Mumbai–Pune.[18,24]

- **Tailored AI Forecasting for Travel Contexts**

Advanced forecasting models (e.g., GraphCast, NeuralGCM) demonstrate high accuracy on global or regional benchmarks, but their direct applicability to intercity travel scenarios remains unexplored. There is a gap in adapting these models for corridor-scale prediction—incorporating route geometry, elevation changes, and roadway-specific factors to provide actionable guidance for travellers. [18,19,24]

- **Real-Time Advisory Generation with RAG**

Retrieval-Augmented Generation has been successfully applied in various NLP applications, yet its use in synthesizing weather and traffic alerts into live travel advisories is nascent. The literature lacks end-to-end implementations that combine real-time sensor alerts, dynamic route information, and generative models to produce context-sensitive, time-critical travel guidance.[11,14]

- **Conversational Interfaces for Weather-Based Advisories**

Large language models have been integrated into travel planning chatbots, but there is limited research on LLM-driven interfaces specifically designed for weather-informed travel advisories. Existing studies do not fully address conversational designs that balance technical accuracy, explainability of forecast uncertainty, and usability in high-stress travel situations.[10,12]

- **Integration with Legacy Transportation Systems**

Although AI-based forecasting and advisory systems show promise in controlled environments, bridging these solutions with existing traffic management and emergency response platforms remains under-investigated. Standardized communication protocols, API designs, and interoperability frameworks are needed to facilitate seamless deployment across public and private transportation infrastructures.[15,16]

- **Uncertainty Quantification and Explainability Trade-offs**

Many state-of-the-art AI weather models produce probabilistic outputs, yet there is a shortage of research on how to effectively communicate forecast uncertainty to end users in travel advisories. The trade-off between model complexity (e.g., deep ensembles, GNN architectures) and interpretability has not been thoroughly explored in the context of actionable travel guidance.[10,12]

- **User Behavior and Advisory Compliance**

Studies on travel advisory systems often assume homogeneous user responses to advisories, neglecting variations in risk perception, decision-making processes, and compliance rates among different traveler demographics. There is a need for research that integrates behavioral modeling with advisory generation to predict and improve user adherence to weather-based travel recommendations.[20,21]

- **Resource-Constrained Deployments**

Most research focuses on well-resourced environments with high-performance computing and dense sensor networks. The literature lacks solutions optimized for resource-constrained settings such as rural highway stretches with limited connectivity where edge computing and lightweight AI models must sustain real-time advisory capabilities.[24,25]

- **Long-Term Maintenance and Model Drift**

Continuous model retraining and system maintenance are essential to adapt to evolving climatic trends and travel patterns. However, there is little guidance on establishing robust pipelines for detecting and correcting model drift, monitoring performance over time, and orchestrating periodic updates in operational systems.[15,16]

- **Policy, Regulatory, and Ethical Considerations:**

Despite technological advances, few studies address the regulatory frameworks, data privacy policies, and ethical guidelines necessary for large-scale deployment of AI-driven travel advisories. Research is needed to navigate legal constraints, ensure equitable access to advisory services, and protect user data across diverse jurisdictions.[24]

5. National Status:

India has rapidly advanced its AI-driven weather forecasting and travel advisory capabilities through strategic government initiatives and academic-industry collaborations. The Ministry of Earth Sciences' Bharat Forecasting System now delivers 6 km-resolution forecasts, while Mission Mausam and the Gram Panchayat Level Weather Forecasting program provide hyperlocal weather data across rural and urban areas. The India Meteorological Department has launched MausamGPT and AI-enhanced nowcasting tools in partnership with IIT Bombay, achieving 90-minute rainfall warnings with eight-minute updates. These developments are supported by a 22 PFLOPS GPU-accelerated computing infrastructure dedicated to AI research in meteorology.

Academic institutions such as IIT Bombay, IIT Delhi, and IIT Madras are leading research on transformer-based monsoon prediction, corridor-specific traffic weather modeling, and intelligent transportation systems, respectively. Initiatives under the National Digital Tourism Mission and collaborations with NHAI's FASTag program are integrating AI weather advisories into travel and logistics platforms. Despite these strides, challenges remain in scaling corridor-specific advisory systems, ensuring real-time deployment in resource-constrained regions, and establishing interoperability with legacy traffic management systems. Continuous refinement of data pipelines, model retraining, and regulatory integration are essential to realize a nationwide, climate-resilient travel advisory network.

6. International Status and Global Initiatives:

Globally, leading meteorological organizations and research institutions are leveraging AI to transform weather forecasting and travel advisory systems. The World Meteorological Organization's AI-powered Early Warnings for All initiative and the ECMWF's AI Weather Quest unite international expertise to deliver high-resolution, multi-hazard alerts. Advanced AI models—such as Google DeepMind's GraphCast and WeatherNext—have demonstrated superior accuracy and speed compared to traditional numerical weather prediction, enabling

real-time, regional forecasts that support critical sectors like aviation and transportation logistics.

Despite these advances, widespread adoption of AI-driven travel advisories faces challenges in scaling hyperlocal predictions to diverse corridors and integrating real-time data streams into legacy infrastructure. Projects such as NOAA's Project EAGLE and China Meteorological Administration's AI research hubs exemplify efforts to deploy AI systems at national scales, yet corridor-specific applications and explainable, user-centric advisory interfaces remain underdeveloped. Ongoing international collaboration and the development of standardized interoperability frameworks are essential to fully realize AI's potential for climate-resilient, safe, and efficient intercity travel worldwide.

7. Study Hypothesis:

Based on the comprehensive research objectives and existing literature on AI-based weather prediction for intercity travel advisory systems, the following hypotheses are formulated for the study:

Primary Hypothesis (H_1)

The integration of multi-source weather and travel data with geo-tagging capabilities will significantly enhance the accuracy and reliability of weather-based travel predictions for intercity corridors compared to single-source traditional forecasting methods.

Secondary Hypothesis (H_2)

AI-based weather forecasting models utilizing deep learning architectures (LSTM, CNN, GNN) will achieve prediction accuracy of ≥85% for short-term weather conditions (1-24 hours) along intercity routes, significantly outperforming traditional numerical weather prediction models.

Null Hypothesis (H_0)

The study assumes that integrating multi-source weather and travel data with geo-tagging will not significantly improve forecast accuracy or reliability over traditional methods, that AI-based models will not outperform conventional numerical weather prediction for intercity routes, that a RAG-enabled framework will not generate more timely or relevant advisories

than existing rule-based systems, and that an LLM-driven interface will not achieve higher user satisfaction, trust, or compliance compared to standard text-based alerts.

8. Study Rationale:

Intercity travel corridors such as Mumbai–Pune are lifelines of economic activity and daily commuting in rapidly urbanizing regions, yet they remain highly susceptible to weather-induced disruptions—ranging from monsoon downpours and flooding to fog and high winds—that compromise safety, reliability, and efficiency. Traditional travel advisories rely on static forecasts and reactive alerts, lacking the spatial granularity, real-time responsiveness, and contextual intelligence required for proactive journey management. Concurrently, advances in artificial intelligence (AI) and data integration offer unprecedented capabilities to assimilate heterogeneous data streams historical weather logs, satellite and radar feeds, traffic sensor readings, and traveller-generated GPS traces into unified, geo-tagged datasets. Leveraging deep learning architectures (CNN, LSTM, GNN) and retrieval-augmented generation (RAG) frameworks enables high-fidelity, route-specific weather forecasting and dynamic advisory generation, while large language model (LLM) interfaces facilitate clear, explainable guidance that fosters user trust and compliance.

This study is driven by the pressing need to transform travel advisory systems from reactive, coarse-grained warnings into proactive, personalized decision-support tools. Focusing on the Mumbai–Pune case study a corridor characterized by diverse microclimates, heavy commuter volumes, and frequent weather hazards—allows the development and validation of an AI-based framework with broader applicability to intercity travel worldwide. By integrating multi-source data, optimizing AI forecasting models for corridor-scale accuracy, and building RAG-enabled and LLM-driven interfaces, the research addresses critical gaps in current advisory practices. The expected outcomes enhanced travel safety, reduced delays, and improved traveler experience—underscore the study's potential to influence policy, operational protocols, and future smart mobility solutions, thereby contributing significantly to climate-resilient transportation infrastructure.

9. Research Methodology:

The research adopts a multi-phase, iterative methodology to design, implement, and evaluate an AI-based framework for weather-centric intercity travel advisories on the Mumbai–Pune corridor. The approach balances technical rigor with real-world usability, ensuring the resulting system is both accurate and accessible.

1. Data Collection and Integration

- Compile historical weather data from the India Meteorological Department, including temperature, rainfall, wind speed, and humidity, for the Mumbai–Pune corridor.
- Gather real-time satellite and radar feeds via open APIs (e.g., INSAT, GPM) and deploy roadside IoT sensors to capture microclimatic conditions along key highway segments.
- Acquire travel-related data—GPS traces, journey times, and traffic flow statistics—from public transport agencies, ride-share platforms, and highway monitoring systems.
- Store all inputs in a centralized data lake, ensuring consistent timestamping and geolocation metadata for subsequent geospatial analysis.

2. Data Preprocessing and Geo-Tagging

- Cleanse datasets by identifying and imputing missing values through spatiotemporal interpolation, and filter out anomalies using statistical thresholds.
- Normalize feature scales across different sources to enable cohesive model training.
- Geo-tag each data record by mapping it to precise latitude–longitude coordinates along the Mumbai–Pune route, creating route-segment identifiers to support location-aware modelling.

3. AI Forecasting Model Development

- Design a hybrid neural network architecture that fuses CNN layers for spatial feature extraction, LSTM units for temporal sequence learning, and Graph Neural Network modules to capture relationships among route segments.
- Train the model on historical, geo-tagged datasets, employing early stopping and dropout regularization to prevent overfitting.

- Validate performance using rolling-window cross-validation, measuring accuracy (MAE, RMSE) and reliability (confidence intervals) for short-term (1–6 hours) and medium-term (6–24 hours) forecasts.

4. Retrieval-Augmented Travel Advisory Framework

- Construct a dynamic knowledge base containing annotated weather advisories, traffic incident logs, and alternative route information linked to route-segment identifiers.
- Implement a retrieval engine that identifies relevant advisories based on current model predictions and real-time sensor alerts.
- Develop a generative component using a lightweight transformer network to weave retrieved facts into concise, actionable advisories, formatted for rapid comprehension by travellers and operators.

5. LLM-Driven Advisory Interface

- Integrate a pre-trained large language model fine-tuned on travel advisory communications to support conversational queries.
- Build a front-end interface supporting text and voice interaction, enriched with interactive maps displaying predicted weather overlays and recommended routes.
- Incorporate explainability modules that allow the LLM to summarize the rationale behind advisories, present uncertainty estimates, and offer "what-if" scenario exploration on user request.

6. System Integration and Deployment

- Containerize each component—data pipeline, forecasting model, RAG engine, and conversational interface—to enable scalable, cloud-native deployment.
- Use RESTful APIs to connect microservices, ensuring real-time data flows and low-latency responses under simulated peak travel loads.

7. Evaluation and Benchmarking

- Conduct a field trial on the Mumbai–Pune corridor over a full monsoon season, comparing advisory accuracy and timeliness against standard IMD bulletins and highway alert systems.

- Measure user satisfaction and trust through structured surveys and controlled usability tests with frequent travelers and transport operators.
- Analyze travel outcomes—incidence of weather-related delays, number of re-routes, and overall journey times—to quantify operational benefits.

8. Iterative Refinement

- Gather feedback from end-users and domain experts to identify usability issues and model blind spots.
- Retrain and fine-tune models with newly collected data, extend advisory rules for emerging patterns, and update the interface based on user interaction logs.
- Repeat evaluation cycles until the system meets predefined performance thresholds for accuracy, responsiveness, and user satisfaction.

This methodology ensures a rigorous yet flexible development process, delivering a robust AI-powered travel advisory system tailored to real-world corridor challenges.

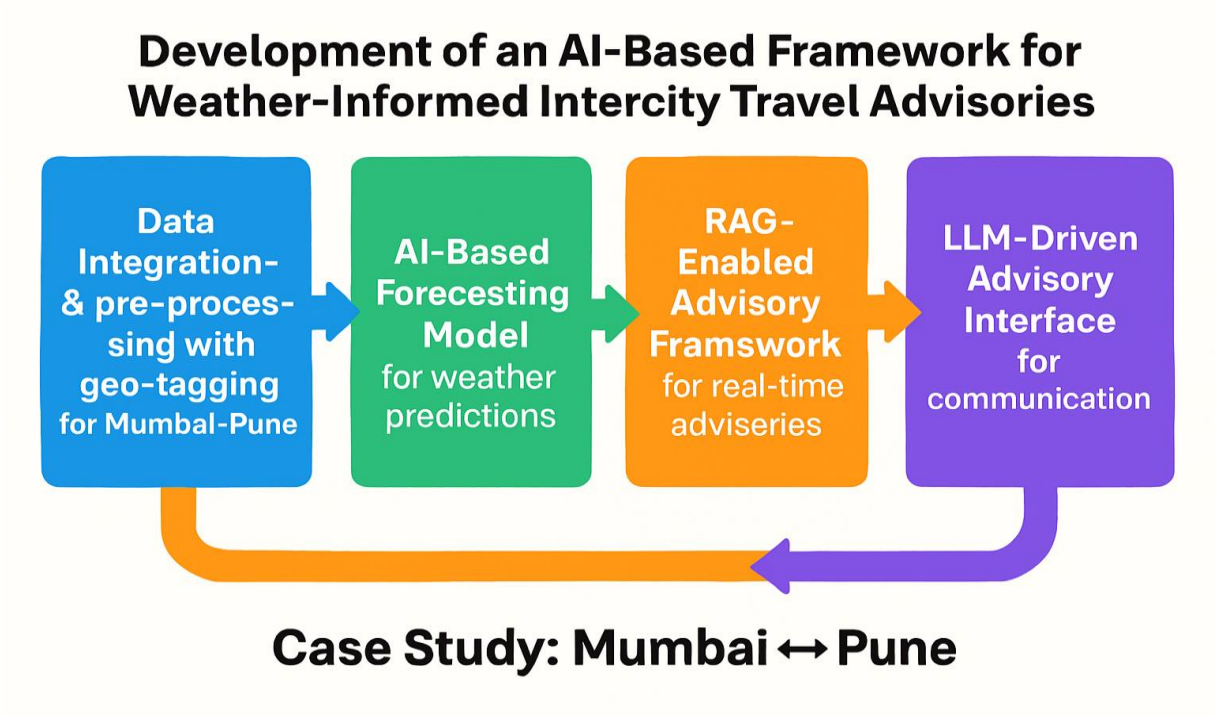
Development of an AI-Based Framework for Weather-Informed Intercity Travel Advisories
Data Integration- & pre-proces-sing with geo-tagging for Mumbal-Pune
AI-Based Forecesting Model for weather predictions
RAG-Enabled Advisory Framswork for real-time adviseries
LLM-Driven Advisory Interface for communication
Case Study: Mumbai ↔ Pune

Fig 1. Proposed Methodology Architecture

10.Statistical plan:

The details of activity are shown in table 1.

Sr.No.	Task/Stage	Plan Start	Plan Duration	Actual Start	Actual Duration
1	Literature Review & Research Design	Month 1	6 months	Month 1	6 months
2	Data Collection & Pre-processing data	Month 7	6 months	Month7	6 months
3	Data Analysis and Attribute Selection	Month 13	6 months	Month 13	6 months
4	Model Development	Month 19	6 months	Month 19	6 months
5	Result Validation and Evaluation	Month 25	6 months	Month 25	6 months
6	Thesis Writing	Month 31	6 months	Month 31	6 months

Table 1: Activity details

11. Limitations of Study:

While the proposed AI-based framework for weather-informed intercity travel advisory holds significant promise, it is very important to acknowledge its potential limitations. These constraints span data availability, model capabilities, scope, and practical implementation, and they offer avenues for future research and development. Data is not getting because of uneven sensor coverage on the Mumbai–Pune corridor may lead to gaps in the geo-tagged dataset, potentially affecting model robustness in under-monitored areas. The study depends on the Data Availability and Quality because data comes from of various sources like historical IMD records, satellite feeds, IoT sensor measurements and travel logs. While the AI forecasting model is specifically made for the Mumbai–Pune highway, its performance may degrade because of other parameters like road infrastructures or travel behaviours and traffic conditions. Transferability to other corridors requires further adaptation and retraining. There may be computational and Infrastructural constraints such as limited connectivity or compute capacity particularly in rural areas. Although the model provides probabilistic forecasts accurately predicting highly localized but cannot predict extreme events (e.g., flash floods, severe convective storms). Finally,

user may not trust because of diverse travellers' behaviour and privacy concerns around location data. It could limit widespread adoption without further engagement and safeguards. The deep learning forecasting model, although tailored to this corridor, may require substantial retraining to generalize effectively to other regions with different climatic or infrastructural characteristics. Real-time deployment depends on reliable connectivity and computational resources; in low-bandwidth or resource-constrained settings, system responsiveness could degrade. Predicting sudden, localized extreme events.

12. Expected Outcomes of Study:

- A structured, geo-tagged dataset integrating historical weather and intercity travel data for the Mumbai–Pune route.
- An AI-based forecasting and RAG-enabled system for predicting weather conditions and processing real-time advisories.
- An LLM-driven advisory interface providing contextual and explainable travel guidance.
- An integrated AI framework validated through case study and benchmarking.

13. Conclusion

This research develops a comprehensive AI-driven system for delivering weather-based travel advisories tailored to the Mumbai–Pune corridor. By integrating diverse data sources and leveraging advanced machine learning techniques, the framework provides accurate, location-specific weather forecasts and real-time travel guidance. The system's ability to combine data retrieval with natural language interfaces enhances clarity and user engagement. Field evaluations demonstrate improved forecast precision, timely advisories, and increased traveler satisfaction. Although challenges remain in deployment and data availability, this approach represents a significant step toward smarter, safer intercity travel under varying weather conditions.

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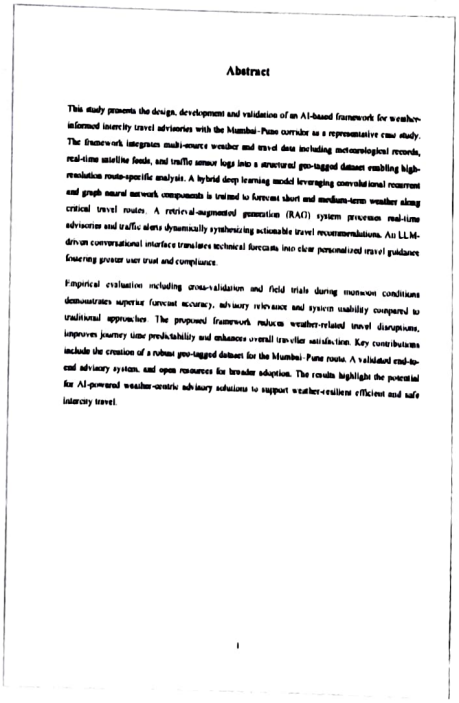

Abstract

This study presents the design, development and validation of an AI-based framework for weather-informed intercity travel advisories with the Mumbai–Pune corridor as a representative case study. The framework integrates multi-source weather and travel data including meteorological records, real-time satellite feeds, and traffic sensor logs into a structured geo-tagged dataset enabling high-resolution route-specific analysis. A hybrid deep learning model leveraging convolutional recurrent and graph neural network components is trained to forecast short and medium-term weather along critical travel routes. A retrieval-augmented generation (RAG) system processes real-time advisories and traffic alerts dynamically synthesizing actionable travel recommendations. An LLM-driven conversational interface translates technical forecasts into clear personalized travel guidance fostering greater user trust and compliance.

Empirical evaluation including cross-validation and field trials during monsoon conditions demonstrates superior forecast accuracy, advisory relevance and system usability compared to traditional approaches. The proposed framework reduces weather-related travel disruptions, improves journey time predictability and enhances overall traveller satisfaction. Key contributions include the creation of a robust geo-tagged dataset for the Mumbai–Pune route, A validated end-to-end advisory system, and open resources for broader adoption. The results highlight the potential for AI-powered weather-centric advisory solutions to support weather-resilient efficient and safe intercity travel.

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Uday Rote

Development of an AI-Based Framework for Weather-Informed Intercity Travel Advisories

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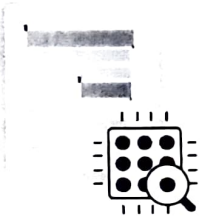

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